Misfortune and Mistake: The Financial Conditions and Decision-Making Ability of High-Cost Loan Borrowers

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The appropriateness of many high-cost loan regulations depends on whether demand is driven by financial conditions ("misfortunes") or imperfect decisions ("mistakes"). Bank records from Iceland show that borrowers have especially low liquidity just before getting a loan. Borrowers exhibit lower decision-making ability (DMA) in linked-choice experiments: 45% of loan dollars go to the bottom 20% of the DMA distribution. Standard determinants of demand do not explain this relationship, which is also mirrored by the relationship between DMA and an unambiguous mistake. Both misfortune and mistake thus appear to drive demand.

I. Introduction

Several forms of consumer credit, including payday loans, deposit advance products, and vehicle title loans, are controversial because they

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are used disproportionately by low-income households and involve high fees. In 2015, lower-income US households spent an estimated $62.7 billion in interest and fees on short-term loan products like these (Schmall and Wolkowitz 2016). Critics call the loans usurious and warn that they take advantage of financially unsophisticated borrowers, who end up in harmful cycles of debt. Proponents describe the high costs of the loans as necessary given the risk to the lender and note that the harm to the borrower of forgoing other obligations or opportunities can be much greater. They argue that these forms of credit provide valuable liquidity to those who struggle to find it elsewhere.

The controversy surrounding high-cost credit and other financial products and services used disproportionately by lower-income households has spurred both regulation aimed at protecting consumers and concern about that regulation.[1] The costs and benefits of this regulation depend on the extent to which demand for these products is because of "misfortune" and "mistake": By *misfortune*, we mean adverse financial conditions that cause customers to place high value on a financial product but also limit its availability at low cost. These circumstances include income, liquidity, and expenditure shocks. By *mistake*, we mean an imperfect choice: a choice that, given the same information, the person would make differently if they attended to it more carefully or had greater ability to assess the factors that determine its payoff.[2] If consumers rely on high-cost credit or other financial products because of misfortune, policy is justified if it reduces market imperfections that limit trade in those products. If they use high-cost credit or other financial products because they

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[1] Several US states have, e.g., prohibited payday loans, placed restrictive caps on the implied interest rates, or instituted "cooling-off periods" to preclude rolling over payday debt (Bhutta, Goldin, and Homonoff 2016). At the federal level, in 2017 the US Consumer Finance Protection Bureau approved rules mandating that lenders underwrite loans to ensure that the borrower can pay them back while meeting basic needs and limiting the number of times lenders can attempt unsuccessfully to withdraw loan payments from a borrower's bank account. The implementation of those rules has since been placed on hold as opponents raise concerns that the regulations impose important burdens on lenders and will reduce the availability of valuable credit. In 2021, the "Overdraft Protection Act" was introduced in the US House of Representatives. The bill would limit the number of overdraft fees a consumer may be charged each month and year and would provide that such fees are reasonable.

[2] This concept of a choice imperfection relates to Gilboa's (2012) definition of rational behavior. In this view, a person's choices are irrational or, in our words, imperfect if he or she thinks of them erroneous after careful explanation, analysis, and consideration of their costs and benefits.

do not properly balance their costs and benefits, then policy should also work to protect consumers from this harm.[3]

This paper links rich administrative data with information from surveys and experiments, all at the individual level, to assess the influence of misfortune and mistake in determining the demand for high-cost credit. Evaluating the role of mistakes is especially challenging because imperfect choices are hard to identify. On the one hand, unobserved constraints, preferences, or beliefs can justify many behaviors as optimal, and caution dictates respect for consumer choice. On the other hand, evidence points to the potential for mistakes. In particular, prior studies show that the choice to use a payday loan is sometimes ill-informed (Bertrand and Morse 2011), may be dominated by cheaper forms of credit (Agarwal, Sumit, and Tobacman 2009), and is often followed by undesirable consequences (Melzer 2011, 2018; Carrell and Zinman 2014; Gathergood, Guttman-Kenney, and Hunt 2019).

In this paper, we address the challenge of distinguishing the consequences of mistakes in three complementary ways. First, using daily records drawn from individual bank and credit card balances and transactions in Iceland, we describe the (changing) financial conditions and behaviors associated with payday loan demand. These administrative data are derived from a financial aggregation app, serving approximately 20% of the Icelandic adult population, which links records from its users' various financial accounts. In that analysis, we document the extent to which the individual circumstances of payday borrowers differ from those of others in the data, how those circumstances change in the days leading up to and following the receipt of a payday loan, and how spending changes upon receipt of the loan.

Second, using the results of experiments conducted via online survey with 1,700 users of the financial aggregator, we capture measures of both economic preferences and decision-making ability (DMA). The experiments involve multiple incentivized choices under risk and uncertainty and about the intertemporal allocation of money. The price variation in these experiments is sufficiently rich to permit well-powered tests of consistency with utility maximization and related normative properties

[3] Note that the use of consumer credit cannot be dismissed as irrational solely on the basis of high costs. The benefits of the spending that the loan enables may outweigh the interest costs. More specifically, assuming that a high-cost loan is the cheapest option available to a consumer, it may be more costly not to take the loan than to face the consequences of not receiving a service, making a purchase, or paying a bill. For example, it is likely rational to take a few hundred-dollar loan if it implies that a consumer can have her car fixed and use it to go to work instead of using more expensive transportation options or pay her electricity bill and cook food at home instead of buying ready-made food. In other words, for small-dollar loans, consumers may be making optimal trade-offs between the spending benefits and high-interest costs.

of choice. Following Choi et al. (2014) and Carvalho and Silverman (2019), we interpret consistency with these normative properties of choice as a measure of financial DMA. In the context of the experiments, consistency with utility maximization means that the participant reveals a single, stable, and sensible objective of the several financial choices he makes while facing varying incentives over a short period of time (Afriat 1967). We interpret revealing such an objective as a reflection of an ability to attend adequately to financial decisions, understand their relevant trade-offs, and map available choices into objectives. This interpretation is supported by evidence in studies showing that these measures are positively correlated with financial success both in experiments and in the field. See Choi et al. (2014), Carvalho and Silverman (2019), and Stango and Zinman (forthcoming).

We then study the relationship between DMA and high-cost loan demand. In individual-level regression analysis, we control for demographic characteristics, granular information on economic circumstances, and measures of time and risk preferences from the experiment. This regression analysis investigates whether, conditional on proxies for standard determinants of financial choices, a measure of DMA has an independent and quantitatively important relationship with high-cost loan demand.

Third, we further evaluate the hypothesis that high-cost loan demand is in part attributable to mistakes by testing an ancillary prediction of that hypothesis. If mistakes caused by lower DMA are in part to blame for high-cost credit demand, then low DMA should also predict other, unambiguous mistakes in the administrative data. The accrual of nonsufficient funds (NSF) fees represents just such an unambiguous mistake. These fees obtain when, in the process of using a debit card to make a purchase, an individual exceeds his or her checking account overdraft limit. Different from costly overdrafts in markets like the United States, there is no benefit to exceeding the limit because the purchase will not be authorized. In this way, a choice that results in an NSF fee is clearly imperfect; it is dominated by the decision not to try to make the purchase. We thus study the relationship between NSF fees and DMA to evaluate further the hypothesis that lower DMA, as measured in the experiment, is, in general, a cause of financial mistakes.

To our knowledge, this is the first study to provide evidence on the relationship between DMA and controversial financial products and services. More generally, it is the first to use administrative bank records to study the relationship between measures of consistency with (normatively appealing) utility maximization and field behaviors and outcomes.

The results from the administrative data alone show that most payday borrowers have only limited access to other forms of liquidity and are, on average, especially illiquid on the day they take the loan. Over the nearly 6 years of observation, payday borrowers maintain, on average, essentially

no liquid assets, and they carry an average of about a month's salary in debt in the form of overdrafts on their checking accounts. Looking back over the 30 days prior to getting a loan, the average of a borrower's checking and savings balances, net of credit card balances, declines steadily until the day the loan arrives and then slowly recovers over the next 3 weeks to levels close to those 30 days prior to the loan. From that point, liquidity starts declining again.

Some prior research has studied the extent to which payday loan demand is attributable to mistake by testing whether borrowers have access to cheaper credit at the time they take the payday loan. Results have been mixed, with some finding large fractions of payday loan borrowers with access to substantial amounts of credit at lower cost (Agarwal, Sumit, and Tobacman 2009) and others finding that the bulk of payday loan borrowers have virtually no cheaper form of market credit available when they take the loan (Bhutta, Skiba, and Tobacman 2015).

In the Icelandic data, which integrate available credit from multiple sources, a majority of payday loan borrowers have little if any cheaper credit available through market sources at the time they take the loan. When she takes out the loan, the median borrower has access to cheaper credit in an amount equivalent to 5 days of her average spending. There is, however, substantial heterogeneity, and 25% of payday loan borrowers have, on the day they receive their loan, access to cheaper credit amounting to more than 3 weeks of average spending.

Taken together, the evidence from the administrative data suggests a substantial but not a dominant role for mistake in driving demand for payday loans. On their own, however, the administrative data results are not dispositive and may be conservative in identifying mistakes. Even among those without access to cheaper credit, the choice to take a payday loan may not be best.[4] To further examine the role of mistakes in the demand for high-cost loans, we therefore relate DMA, as measured in the experiments, to demand for payday loans.

Payday loan borrowers exhibit substantially lower DMA in the experiments, and those with low ability play an outsized role in the market for payday loans. In these data, 29% of payday loan dollars are lent to the bottom 10% of the DMA distribution, and 45% are lent to the bottom 20% of the distribution. In individual-level regression analysis, the relationship between DMA and high-cost loan demand is not explained by

[4] The administrative-data results may also be conservative in identifying mistakes if a lack of access to cheaper credit is itself the product of prior mistakes. An important example is the limited access to cheaper credit that results from having taken out a payday loan in the past. If an earlier decision to take a payday loan was a mistake, then an individual's current access to cheaper credit, interpreted as evidence of misfortune in our analysis, would in fact be a consequence of an earlier mistake.

demographic characteristics, granular information on economic circumstances, or measures of preferences from the experiment.

The third part of our analysis shows that DMA measures are correlated with an unambiguous mistake, NSF-fee accrual. Conditional on demographic characteristics, economic preferences, and financial conditions, those with lower DMA incur significantly more NSF fees. This evidence is consistent with the hypothesis that mistakes caused by lower DMA are in part to blame for high-cost credit demand.

Finally, we evaluate the external relevance of the Icelandic findings and the potential for relying on survey data alone to do similar analyses by comparing, to the extent possible, the relationships estimated there with those estimated from a survey of US consumers. The US survey data on economic outcomes are self-reported, and the measures of high-cost credit take-up, preferences, and DMA are relatively coarse. Nevertheless, we find that the relationship between DMA and the probability of receiving a payday loan is very similar in these US data and in the Icelandic data.

The linked administrative and experimental measures from Iceland, augmented by US survey data, thus indicate that both misfortune and mistake are important for the demand for high-cost consumer credit and the incidence of NSF fees. Our analysis does not provide a quantitative assessment of the net welfare consequences of this form of credit. It does not describe optimal policy. Instead, these results provide evidence that intervention aimed at consumer protection in these markets is justified. The findings indicate that policy should be concerned with both the possibility that market imperfections limit trade and, at the same time, the possibility that mistakes lead to excessive levels of trade in both high-cost consumer credit and avoidable bank fees.

II. Related Literature

This paper contributes to a literature on high-cost credit, the financial conditions of borrowers in those markets, and the consequences of access to these loans. Prominent examples from that literature include Agarwal, Sumit, and Tobacman (2009), Zinman (2010), Melzer (2011, 2018), Bertrand and Morse (2011), Morse (2011), Bhutta, Skiba, and Tobacman (2015), Bhutta, Goldin, and Homonoff (2016), Dodbridge (2016), Skiba and Tobacman (2019), and Gathergood, Guttman-Kenney, and Hunt (2019). Our paper is distinguished from the bulk of that literature by its use of comprehensive, high-frequency, administrative data on the balances and transactions of the study sample that reveal the liquidity patterns of loan recipients. Prior studies with access to administrative data have used credit files to observe debt and the availability of other sources of credit but not a comprehensive overview of the personal finances of the consumer over a long period of time. In this way, we obtain a granular view of the

financial circumstances of high-cost credit users. Our analysis of the administrative data thus provides new evidence on the importance of misfortune in driving demand for these loans.

As we do, Allcott et al. (2022) evaluate whether decisions to take high-cost loans are imperfect and whether consumer protection in that market is thereby justified. Their paper conducts an innovative experiment to elicit both the beliefs of payday loan borrowers about the likelihood of future borrowing and their willingness to pay for a $100 incentive to avoid future borrowing. The responses in these experiments are then linked to administrative records on payday loan borrowing and used to estimate the structural parameters of a model and conduct welfare analysis. In their model, imperfect choice is identified with time-inconsistent preferences or mistaken beliefs about those preferences and the future take-up of loans. Our approach integrates more information about the borrower's balance sheet and puts less structure on the mechanisms behind imperfect choice. In this way, we can accommodate more sources of choice imperfection but cannot make the quantitative welfare assessments that Allcott et al. (2022) can.

Our reliance on administrative records from a financial aggregator relates to a growing literature that uses these kinds of data to study a variety of phenomena. Examples include Gelman et al. (2014, 2018), Baker (2018), and Kueng (2018). In particular, these Icelandic data have been used to study the dynamics of liquid asset holdings and spending in response to income (Olafsson and Pagel 2018), how different generations use financial products to manage their finances (Carlin, Olafsson, and Pagel 2019), and how consumers use credit lines in response to transitory income shocks (Hundtofte, Olafsson, and Pagel 2019).

Our interest in measuring consistency with utility maximization and relating it to observable characteristics and behavior connects our work to the literature that has developed different measures of economic rationality (Dean and Martin 2016; Halevy, Persitz, and Zrill 2018; Polisson, Quah, and Renou 2020; Echenique, Imai, and Saito 2023) and a literature that has used such measures to study the correlates and determinants of rationality (Kim et al. 2018; Banks, Carvalho, and Perez-Arce 2019; Carvalho and Silverman 2019). Our analysis draws on elements of this literature in its use of recent advances in revealed-preference tests of (the degree of) consistency with different axioms of choice. It is also, to the best of our knowledge, the first to use administrative bank records to relate measures of consistency with (normatively appealing) utility maximization to field behaviors and outcomes.

A link between experiments and comprehensive administrative records is rare in the broad stream of research that seeks to understand the fundamentals of economic behavior through financial data. To our knowledge, the closest analogue is Epper et al. (2020), which links experiments

to yearly snapshots of assets and liabilities, and no other study has linked experimental economic data to comprehensive and high-frequency bank data at the individual level. As important, our analysis not only allows for heterogeneity in (nonstandard) economic preferences but also considers the importance that violations of utility maximization may have in understanding financial decisions (Choi et al. 2014; Stango and Zinman forthcoming).

III. Background: Consumer Credit in Iceland

In many countries, credit cards are a leading source of revolving credit to consumers. In other countries, including Iceland, revolving consumer debt most commonly takes the form of overdrafts on checking accounts. Virtually all checking accounts in Iceland offer an overdraft facility, the size of which is based on credit history, income, and assets. Overdrafts can be made at any time without consulting the bank, and overdraft status can be maintained indefinitely (subject to ad hoc reviews). Overdrafts dominate the unsecured consumer credit market, representing approximately 10% of all household loans during 2011–2017, and they charge average annual percentage rates (APRs) of around 12%.[5]

While overdraft facilities on checking accounts are the primary source of revolving credit in Iceland, access to high-cost, short-term loans has grown substantially in recent years. Payday loans were first offered in Iceland in 2009. They require only a minimal credit assessment, are for short terms, and are available almost immediately after application in potentially substantial amounts. To obtain a loan, individuals need to (i) affirm their legal competence to manage their financial affairs, (ii) provide the Icelandic equivalent of the Social Security number, (iii) be formally registered as living in Iceland, (iv) supply an active email address/phone number and an active debit card number, and (v) not be undergoing debt mitigation. While they are called "payday loans," obtaining this form of credit in Iceland requires no documentation of employment or the timing of paydays. Lending periods are flexible; individuals can choose durations between 1 and 90 days. Payday lenders operate only online or by short message service (SMS). Upon successful application, loans are deposited in the borrower's bank account within a few minutes. The total borrowing limit of the five providers active during the period covered by our sample was the equivalent of approximately $6,000.

Oversight of Iceland's payday loan market is weak. For regulatory purposes, payday lenders are not classified as financial institutions, they do

[5] Statistics, Central Bank of Iceland (www.sedlabanki.is/library/Fylgiskjol/Hagtolur/Fjarmalafyrirtaeki/2019/1013\20INN_Utlan_052019.xlsx).

not need an operating license, they are all headquartered abroad, and government supervision of their activities is limited. Indeed, payday lending was effectively unregulated in Iceland prior to 2013.

Due in part to the lack of government oversight, systematic evidence about the costs of payday loans in Iceland is limited. Kristjánsdóttir (2013) documents the costs of payday loans by all the Icelandic payday providers in 2013 and compares the costs of payday loans to those in other Nordic countries and the United Kingdom. This comparison shows that in 2013 the APR of payday loans was higher in Iceland than in the other countries, with APRs starting at approximately 2,800%.

In November 2013, Iceland's Consumer Loans Act no. 33/2013 capped the APR on consumer debt at 50 percentage points above the Central Bank of Iceland's key interest rate. There is no evidence, however, that this regulation was binding on the costs of payday loans. Payday lenders appear to have circumvented or ignored the regulation. Some lenders skirted the law by, for example, having borrowers purchase e-books in exchange for expedited loan processing. Such fees are not included in the calculation of the APR. Others either ignored the law or interpreted their fees as exempt from it. To illustrate, appendix figure 5 (app. figs. 1–8 and app. tables 1–15 are available online) shows an example of a payday loan contract and a screenshot from the home page of one of the payday loan providers. These examples were collected by Iceland's Ministry of Tourism, Industry, and Innovation in 2018. The figure shows that the APR charged on a 30-day loan was 3,448.8%, very similar to the APRs documented by Kristjánsdóttir (2013) prior to the act. Consistent with the view that the regulation was not binding for payday lenders, we find no evidence in the administrative data of a discontinuous change in the number or size of loans around November 2013—see appendix figure 6.

Information on the size of the payday lending market in Iceland is limited. To the best of our knowledge, ours is the first study to compare the use of payday loans to the use of other sources of consumer credit and relate it to other financial behavior in Iceland. Approximately 5.6% of the consumers in our data used payday loans at least once during a period of 6 years. Thus, as in other developed economies, payday borrowing is relatively uncommon, but the magnitude of borrowing among those who use payday loans users is substantial and seems likely to have an important influence on their financial circumstances.[6]

[6] This is consistent with statistics from the Debtors' Ombudsman of Iceland for debt mitigation which show that the share of people aged 18–29 who have applied for debt relief has increased sharply in recent years, and payday loans account for a much larger proportion of these troubled borrowers' total obligations. By 2017, 70% of debt mitigation applicants aged 18–29 owed payday loans. Among applicants who had payday debt, it accounted for about 20% of their total debt (Central Bank of Iceland 2018).

IV. Administrative Data

We use data from Iceland gathered by Meniga, a financial aggregation software provider to European banks and financial institutions. Its account aggregation platform allows bank customers to view and manage all their bank accounts and credit cards across multiple banks in one place. Each day, the software automatically records all the bank and credit card transactions, including descriptions and balances of credit cards, checking accounts, and savings accounts, and overdraft and credit card limits. Additionally, the data contain demographic information, such as age and gender.

Anyone who has an online bank account in Iceland can register at meniga.is to access the personal financial management platform. Furthermore, all larger banks in Iceland allow their customers to sign up directly through their internet bank. All who sign up agree to be a part of a sample for analytical purposes. In January 2017, the Icelandic population was 338,349 individuals, of whom 262,846 were older than 16. At the same time, Meniga had 50,573 users, which is about 20% of the adult population. Their service is marketed through banks, which partly addresses concerns about the representativeness of the sample—see table 4.

We restrict our analysis sample to users for whom we observe income and demographic information and whose expenditure data is credible.[7] In our analysis, we use five different types of information from the administrative data. First, we use the amounts and dates of payday loans. Second, we use the daily balances of checking accounts, savings accounts, and credit cards, and overdraft and credit card limits. Third, we use transaction-level information on income receipts, including the date of receipt and the income source, which we use to calculate monthly salary and monthly income. Fourth, we use information on the number of NSF charges each month. Finally, we use transaction-level information on spending. The different pieces of information are available for different periods. Data on payday loans are available from January 1, 2011 to January 31, 2017. Information on daily balances is available from September 1, 2014 to February 13, 2017. Income is available from January 6, 2011 to February 19, 2017, expenditures from January 1, 2011 to March 2, 2017, and NSF charges

[7] The credibility of expenditure data depends on how well integrated a user is with Meniga. When a user signs up, he agrees to import two years of transaction history into the Meniga database. If a user does not import all of his accounts in use, his financial activity will reflect that. We can therefore detect whether accounts in use are not linked by imposing a minimum data activity criterion that is captured by the following requirements: the user must (1) be active for at least 23 out of 24 months, (2) have been active for the past 3 months, and (3) have at least five transactions in food (groceries or dining out). After applying these filters, comparison with the Statistics Iceland consumption index and with credit card transactions indicates that the spending captured by the platform is comparable to that in other sources.

from January 2011 to February 2017 (these are reported on a monthly basis).

After applying the filters, we have data for 12,747 Meniga users, of whom 717 have taken at least one payday loan during the 6 years of observation.

A. *Preliminary Statistics*

Table 1 shows summary statistics of the Meniga sample regarding payday loans. All monetary figures shown in the paper are in hundreds of Icelandic króna (kr). In 2017, 100 kr corresponded approximately to 1 US dollar. Therefore, the reader can treat the monetary figures as US dollars. Restricting attention to loans of $10 or more, the mean and the median of loans are approximately $250 and $200. During the 6-year period of the data, payday loan borrowers took an average of 20 loans. The median borrower took 10 loans and borrowed $2,240.[8]

Table 2 compares payday loan borrowers to nonborrowers. Borrowers earn less and have less money in their checking and savings accounts. Some borrowers have relatively high incomes, however. The 90th percentile of the distribution of monthly income after taxes is approximately $5,000. The typical borrower has no money in her savings account and is overdrawn by $1,291. Borrowers also have lower credit card balances, which partly reflects that they have lower credit card limits (not shown in the table).[9]

B. *Patterns of Liquidity*

Most payday borrowers have little liquidity, and figure 1 shows that they are typically more illiquid in the days leading up to getting the loan. The figure shows the average liquidity—that is, the sum of savings and checking account balances, overdraft limit, and credit card limit minus balance—as a fraction of the long-run, individual-level average of daily spending, before and after the loan was taken. Liquidity gradually declines by about 4 days of spending until the day the loan is taken. Liquidity then temporarily bounces back to the original level. After the recovery, liquidity starts falling again.

[8] The data do not contain information on the specifics of each loan. Rather, whenever an individual received money or made a payment to a payday loan firm, we observe the amount and the date of the transaction. Under some assumptions, we can use these data to try to infer APRs, delinquency rates, and maturity. We estimate that APRs are greater than 800% (at the time the average overdraft APR was 12%). Individuals seem to typically pay about $60 in fees and interest-rate charges for a loan of $200. The median maturity is 12 days. The evidence suggests high delinquency rates, but certainly lower than 50%. Indeed, according to Iceland's Ministry of Tourism, Industry, and Innovation (2019), the delinquency rate of payday loans in 2017 was around 15%–20%.

[9] Appendix table 12 shows summary statistics of overdraft and credit card usage.

TABLE 1
SUMMARY STATISTICS OF PAYDAY LOANS

		PERCENTILES				
	MEAN	10th	25th	50th	75th	90th
Amount individual loans (kr)	249	100	130	200	300	400
Among payday loan borrowers:						
Number of payday loans	20	1	3	10	26	50
Total amount borrowed (kr)	4,876	200	600	2,240	5,650	12,780

NOTE.—This table shows summary statistics for 12,556 individual payday loans taken by 641 borrowers. The sample is restricted to loans of $10 (~1,000 kr) or more.

Focusing on just the day before the loan is taken, table 3 shows that many payday borrowers have no access to cheaper liquidity when they take loans.[10] At the median, even if a payday borrower reaches her overdraft limit, withdraws all her savings, and maxes out her credit cards, she can draw just 5 days of spending. There is, however, substantial heterogeneity. Some payday borrowers have cheaper alternatives. In particular, those in the 75th and 90th percentiles have about 8 and 30 average days of spending, respectively, available to them if they borrow via overdraft and tap into their savings. If we include what is possible to borrow on credit cards, this upper part of the distribution can borrow at least 3 weeks' worth of average spending at lower interest rates. This segment of the borrowing population appears to be making imperfect decisions in using credit that is more expensive than necessary.

V. Experimental Protocols

Analysis of the administrative data alone indicates that misfortune is a primary driver of demand for high-cost credit but that mistakes also play a role. Payday borrowers in Iceland tend to have lower income and low liquidity, on average. They also tend to be more illiquid in the days just before receiving the loan. While some of this illiquidity might be the product of earlier mistakes, perhaps even an earlier decision to take a payday loan, a simple test for dominated choices provides evidence that, for most borrowers, this is not the case. Only 25% of borrowers have access to at least a week's worth of spending in cheaper liquidity and thus reveal a clear role for mistake in driving demand for payday loans.

The evidence on liquidity favoring misfortune may, however, be conservative because, even among those who have no access to cheaper market credit, the choice to take a payday loan may not be best. Indeed, many people with low income and liquidity choose not to borrow from payday

[10] Figure 1 and table 3 provide slightly different estimates of the average liquidity 1 day before the loan is taken because the former adjusts for when the interval between two loans is shorter than 30 days and nets out day-of-the-week and calendar-day-of-the-month effects.

TABLE 2
SUMMARY STATISTICS OF INCOME, CHECKING, SAVINGS, AND CREDIT CARDS

		PERCENTILES				
	MEAN	10th	25th	50th	75th	90th
Monthly salary:						
Nonborrowers	5,013	853	1,652	2,973	4,627	6,718
Borrowers	2,378	855	1,332	2,133	3,012	4,091
Monthly income:						
Nonborrowers	5,931	1,295	2,219	3,635	5,386	7,654
Borrowers	3,074	1,315	1,919	2,799	3,872	5,092
Checking balance:						
Nonborrowers	−226	−6,246	−1,662	187	1,233	3,618
Borrowers	−3,121	−8,867	−5,087	−1,291	29	334
Savings balance:						
Nonborrowers	3,744	0	0	3	929	7,250
Borrowers	456	0	0	0	21	617
Credit card balance:						
Nonborrowers	1,531	0	168	1,147	2,267	3,540
Borrowers	748	0	0	0	971	2,262

NOTE.—This table shows summary statistics for payday loan borrowers ($N = 596$ for salary and income and $N = 594$ for balances) and for nonborrowers ($N = 12{,}006$ for salary and income and $N = 11{,}074$ for balances). Monthly salary and monthly income correspond to the individual's average monthly salary and average monthly income between February 2011 and January 2017. The balances correspond to the individual's median daily balances between September 1, 2014 and February 13, 2017.

lenders, and even those who turn to payday loans when they are especially illiquid do not always do so.

To further examine what underlies the heterogeneity in decisions to take payday loans, and evaluate the role of mistakes, we therefore relate preferences and DMA as measured in the experiments to demand for payday loans.

A. *Recruitment and Survey Design*

Meniga sent a subset of its clients in Iceland an email with an invitation and a link to an online survey that we designed and programmed. They successfully delivered 8,913 email invitations to users with complete records. Of those, 1,701 (19.8%) completed the survey. Compared with similar studies, this is a relatively high response rate. Epper et al. (2020), for example, report 13%, and Andersson et al. (2016) report 11%.

The survey contained three experimental tasks—a risk, an ambiguity, and an intertemporal choice task—and a brief questionnaire with questions about education, household composition, assets, and debt. Participants earned on average $25 for their participation and for the incentives. Payments ranged from $5 to $63 with a median payment of $18. We discuss our sample and then the experimental tasks in detail.

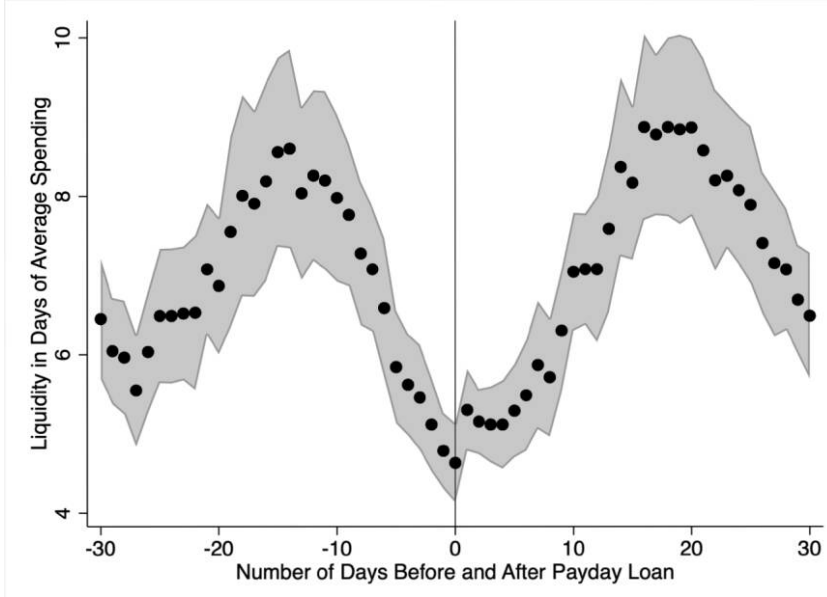

FIG. 1.—Patterns in liquidity around payday loans. The figure shows a time-event study of median liquidity in days of average spending 30 days before and 30 days after a payday loan was taken. The analysis uses data on payday loans taken between October 1, 2014 and January 14, 2017 because the data on checking, savings, and credit card accounts are available for the period between September 1, 2014 and February 13, 2017. 3,453 payday loans were taken between October 1, 2014 and January 14, 2017 by 311 participants.

B. Sample

Table 4 compares the survey sample to a nationally representative sample. Statistics Iceland reports that in 2017 the average age among those above age 15 was 45.3, and that women constituted 50% of the population. The average age in the survey sample is 43.5, and the share of women is 47%. The share of singles in our survey is lower and the share of individuals

TABLE 3
LIQUIDITY 1 DAY BEFORE TAKING PAYDAY LOAN

		PERCENTILES				
	MEAN	10th	25th	50th	75th	90th
Checking balance + overdraft limit (1)	5	0	0	1	4	13
Savings balance (2)	11	0	0	0	0	10
Credit card limit − credit card balance (3)	10	0	0	0	7	29
(1) + (2)	16	0	0	1	8	30
(1) + (2) + (3)	26	0	1	5	23	61

NOTE.—This table shows summary statistics of daily balances as a fraction of average daily spending borrowers had 1 day before they took payday loans. The number of payday borrowers is 322, and the number of loans is 3,672.

TABLE 4
COMPARISON OF SURVEY SAMPLE TO ICELANDIC POPULATION

	SURVEY PARTICIPANTS	ICELANDIC POPULATION
Female (%)	47	50
Age (years)	43.5	45.3
Labor income (kr)	4,343	4,153
Family composition (%):		
Spouse	29	28
Single	23	42
Spouse and children	43	25
Single and children	6	5
Highest degree obtained (%):		
Mandatory education	9	39
Journeyman's examination	4	5
Master of a certified trade	3	6
Matriculation examination	11	8
Tertiary education	8	15
Technical degree	5	2
Bachelor	30	15
Master	30	7
Ph.D.	2	1
Other	0	3

NOTE.—This table compares survey participants to the general Icelandic population.

living with a spouse and children higher than in the overall population. Besides selection, this discrepancy may also be explained by the fact that individuals who live with a spouse (and possibly children) but are not registered as such are counted by Statistics Iceland as living alone.

Table 4 also compares the education of our sample to the education of the Icelandic population. The largest difference is in the share of individuals who have completed only mandatory education. The difference may be partly explained by differences in measurement. Statistics Iceland receives information on graduates directly from Icelandic educational institutions. This means that degrees obtained abroad are not registered. Icelanders who get university degrees abroad, which is common, would be registered as having completed only mandatory education.

Appendix table 4 compares the survey sample to Meniga users with complete records. Despite the large sample size of the administrative data, we cannot reject the hypothesis that these two groups have similar liquidity, income, and demand for payday loans. There are some differences, however, in the number and amount of NSF charges.

C. Experimental Tasks

1. Risk Task

Participants allocated an experimental endowment of 500 kr (approx. $5) across two or five risky assets. The assets paid different amounts depending

on whether a ball drawn from an urn was black or white. Participants were informed that the urn had five black balls and five white balls. Their decisions involved choosing how much to invest in each asset. Participants were presented with 15 investment problems (one of the 15 problems was randomly selected for payment). In the first eight investment problems, there were two assets. In the last seven investment problems, there were five assets. We varied the asset returns across the investment problems.

To illustrate, appendix figure 1 shows a screenshot of the interface presented to participants for the problems with two assets. The table at the top of the screen shows the returns of assets A and B per 1 kr invested. Each participant was then prompted to make her investment choices. The graph below the table displays two bars: the first bar shows the amount invested in asset A, and the second bar shows the amount invested in asset B. Participants made their investments either by dragging the bars up and down or by clicking on buttons labeled with plus and minus signs. The interface was such that participants always invested 100% of their experimental endowment. A similar interface was used in the investment problems with five assets (see app. fig. 2). The only distinction was that participants were shown information about five assets—A, B, C, D, and E—and the graph displayed five bars.

Half of the participants were randomly selected to be offered the option of avoiding the investment problem (Carvalho and Silverman 2019). These participants were offered a choice between making the investment decision or taking an outside option of −50 kr, 0 kr, or 100 kr. The amount of the outside option was varied across the investment problems. The participant was paid this amount if she selected the outside option in the problem ultimately selected for payment. Appendix table 1 shows the parameters of the 15 decision problems.

The interfaces for the participants with the outside option were slightly different. Appendix figure 3 shows a screenshot. It differed from the interface used by other participants (app. fig. 1) in two ways. First, the graph with the bars was not shown. Second, the prompt to invest ("You will choose the amount you want to invest on each asset.") was replaced by a prompt for the participant to choose between investing the experimental endowment (a button labeled "Invest *Y* kr.") and taking the outside option (a button labeled "Receive *X* kr."). If she clicked on the first button, the bars were unveiled and she could make her investment choices using the same interface used by other participants. If she clicked on the second button, she saw the next decision problem.

2. Ambiguity Task

The ambiguity task was similar to the risk task with three distinctions. First, participants were informed that the urn now had eight balls of one

color and two balls of the other. However, they did not know whether the urn had eight black balls and two white or if it had two black and eight white. Second, in all 15 investment problems, there were just two assets. Third, participants were not offered the option of avoiding the investment problem. Appendix table 2 shows the parameters of the 15 investment problems. As in the risk task, one of the 15 problems was randomly selected for payment.

3. Intertemporal Choice Task

Participants had to allocate their experimental endowment across a sooner date and a later date. The amount allocated to the later date accrued an experimental interest rate. Participants were presented with 12 intertemporal allocation problems (one of the 12 problems was randomly selected for payment). We varied the experimental endowment, the experimental interest rate, and the sooner date across the problems. In the first six problems, the sooner date was today. In the last six problems, the sooner date was 1 year away. The time interval between the sooner and later dates was always 1 month. Within a time frame, the interest rate increased monotonically. Appendix table 3 shows the parameters of the 12 intertemporal allocation problems.

Appendix figure 4 shows a screenshot of the interface for the intertemporal choice task. Two calendar sheets at the top of the screen show the sooner date (*left*) and the later date (*right*). The graph below the calendar sheets displays two bars: the bar on the left shows the amount to be received at the sooner date; the bar on the right shows the amount to be received at the later date (including the interest accrued).

4. Measuring DMA

Our main measure of DMA is a composite that reflects the internal consistency of choices in the risk and ambiguity tasks. We exploit the within-subject variation in asset returns to construct individual-specific measures of DMA for each task. In the ambiguity task, we study whether choices violate the generalized axiom of revealed preference (GARP).[11] In the risk task, we use different measures depending on whether the participant had the option to avoid the investment problem. We study whether the choices of those with the option to avoid the investment problem violate monotonicity with respect to first-order stochastic dominance (FOSD)

[11] In the intertemporal choice task, we calculated Critical Cost Efficiency Index (CCEI; Afriat 1972) separately using the choices for a given time frame and then took the minimum of the CCEI across the two time frames.

and whether the choices of those without such option violate GARP and FOSD (Polisson, Quah, and Renou 2020).

Choi et al. (2014) and Kariv and Silverman (2013) argue that consistency with GARP is a necessary condition for high-quality decision-making. This view draws on Afriat (1967), which shows that if an individual's choices satisfy GARP in a setting like the one we study, then those choices can be rationalized by a well-behaved utility function. Consistency with GARP thus implies that the choices can be reconciled with a single, stable objective. We assess how nearly individual choice behavior complies with GARP using Afriat's (1972) CCEI. The CCEI is a number between 0 and 1, where 1 indicates perfect consistency with GARP. The degree to which the index falls below 1 may be viewed as a measure of the severity of the GARP violations.

Consistency with GARP may be too low a standard of DMA because it treats all stable objectives of choice as equally high-quality. A stronger requirement would require monotonicity of preferences. Specifically, violations of monotonicity with respect to FOSD—choices that yield payoff distributions with unambiguously lower payoffs than available options—may be seen as errors and provide a criterion for decision-making quality.[12]

We use the distribution of possible payoffs to assess how closely individual choices comply with this dominance principle. To illustrate a violation of FOSD, consider a simplified case with two assets and no outside option. Asset 1 pays B if a black ball is drawn and 0 if a white ball is drawn. Asset 2 pays 0 if a black ball is drawn and W if a white ball is drawn. Let a be the amount invested on asset 1. The remaining $500 - a$ is invested on asset 2. Investing a^{RF} on asset 1 and $500 - a^{RF}$ on asset 2 is the risk-free allocation that pays the same amount irrespective of the color of the ball drawn, that is, $a^{RF}B = (500 - a^{RF})W$.

Suppose that asset 1 has a higher return than asset 2, that is, $B > W$, and that a participant chooses to invest less on asset 1 than the amount invested in the risk-free allocation, that is, $a < a^{RF}$. In this case, investing $a' = 500 - aB/W$ on asset 1 yields an unambiguously higher payoff distribution than investing a on asset 1. First, notice that the minimum payout when investing a (black ball is drawn) is equal to the minimum payout when investing a' (white ball is drawn): aB. Second, the expected return

[12] Our approach to measuring DMA is related to von Gaudecker, van Soest, and Wengström (2011). That paper also studied behavior in choice experiments but estimated a flexible parametric model that includes an individual-level parameter ω_i that gives the propensity of individual i to choose randomly rather than on the basis of preferences. That parameter can be interpreted as an individual measure of DMA as it captures a tendency for an individual to be consistent both with rationality and with some assumptions about the functional form of utility. This is different from our approach in that, rather than make additional assumptions about the structure of preferences, we rely only on consistency with utility maximization and on consistency with monotonicity.

of investing a', $250 + a'(B - W)/2$, is higher than the expected return of investing a, $250 + a(B - W)/2$, because $B > W$ and $a' > a$.

Following Choi et al. (2014), we calculated a FOSD score as follows. If the selected investment portfolio was dominated as in the example above, the FOSD score was calculated as

$$\frac{250W + a(B - W)/2}{250W + a'(B - W)/2},$$

which equals the expected return of the selected allocation as a fraction of the maximal expected return. The availability of the outside option introduces more opportunities for violating FOSD. First, if the participant invests $a < a^{RF}$ on asset 1 and the outside option is greater than $250 + a(B - W)/2$, then investing a is dominated both by investing $a' = 500 - aB/W$ and by the outside option, in which case we calculated the FOSD score as

$$\frac{250W + a(B - W)/2}{\max\{250W + a'(B - W)/2,\ \text{outside option}\}}.$$

Second, the participant violates FOSD by investing $a > a^{RF}$ if the outside option is greater than $250 + a(B - W)/2$—in this case we calculated the FOSD score as

$$\frac{250W + a(B - W)/2}{\text{outside option}}.$$

Finally, one violates FOSD by taking the outside option if it is lower than the risk-free return, $250 + a^{RF}(B - W)/2$, in which case the FOSD was calculated as

$$\frac{\text{outside option}}{250 + a^{RF}(B - W)/2}.$$

The FOSD score was assigned a value of 1 if there was no FOSD violation.

We also calculate a unified measure of violations of GARP and of monotonicity with respect to FOSD, following Polisson, Quah, and Renou (2020). This measure, like the CCEI, lies between 0 and 1, where 1 represents perfect consistency with both GARP and monotonicity with respect to FOSD.

To reduce the influence of measurement error on estimates, we constructed a composite measure of DMA derived from the risk and ambiguity tasks. We first calculated participants' percentile ranks in the distribution of DMA in each task. For the risk task in particular, we calculated separate percentile ranks for those participants who had the option of avoiding the investment problem and those who did not. For the first group, we calculated their percentile ranks in the distribution of the measure

of FOSD violations. For the second group, we calculated their percentile ranks in the distribution of the unified measure of GARP and FOSD violations. Finally, we constructed a DMA index as the first component of a principal component analysis of the measures of DMA in each one of the two tasks.[13]

In section VI, we assess the validity of this index by evaluating its ability to predict an unambiguous mistake revealed in the administrative data. That mistake, the accrual of NSF fees, which produce no benefit to the consumer, is strongly correlated with this principal component index of consistency with utility maximization.

As an alternative to the principal component approach to measurement error, we adopt the obviously related instrumental variables approach (ORIV; see Gillen, Snowberg, and Yariv 2019). That approach uses DMA derived from the risk task as an instrument for the DMA derived in the ambiguity task while also using the ambiguity DMA to instrument for the risk DMA. See appendix table 5 for details. The two approaches produce qualitatively similar results.

D. Measuring Time and Risk Preferences

To avoid a multiple-indicators problem and better distinguish between DMA and preferences, both time preferences and risk preferences, identified with the curvature of the utility function, are derived from the intertemporal choice task.[14] Let $s^0_{i,r}$ be the fraction of the endowment allocated by participant i in the intertemporal choice task to the sooner date when the sooner date is today and the interest rate is r, and let $s^1_{i,r}$ be the fraction allocated by i to the sooner date when the sooner date is 1 year away. We measured i's impatience as the average of $s^1_{i,r}$ across the five different positive r's. Define $\Delta_{i,r} \equiv s^0_{i,r} - s^1_{i,r}$. We measured the present bias of i as the average of $\Delta_{i,r}$ across all six r's. Participant i was classified as present biased if this average was positive, time consistent if 0, and future biased if negative. Define $d^k_{i,r,r'} \equiv (s^k_{i,r} - s^k_{i,r'})/(r' - r)$ for $k = \{0,1\}$. The intertemporal elasticity of substitution was measured as the average of $d^k_{i,r,r'}$ across the five interest-rate increases and across k. Curvature of the utility function is defined as the inverse of the intertemporal elasticity of substitution. We show in appendix table 6 that we obtain similar results if we use a measure of risk aversion constructed from the risk task.

[13] The first principal component explains about two-thirds of the variation. It loads equally on the DMA from the risk task and the DMA from the ambiguity task such that it is virtually equivalent to taking an average of the two.

[14] Participants very rarely violated GARP in the intertemporal choice task, which gives us greater assurance that we are capturing preferences rather than a mix of preferences and DMA.

In appendix table 7, we assess the validity of these measures of preferences by evaluating whether they reproduce associations documented in previous work. The table shows that they predict the relevant outcomes in expected ways: impatience predicts wealth (as in Epper et al. 2020); present bias predicts consumer debt (as in Meier and Sprenger 2010); and risk aversion predicts stock market participation (as in Barsky et al. 1997).[15]

VI. Experimental Results

Those who exhibit lower DMA in the experiments make greater use of payday loans. Figure 2 shows averages of the number of payday loans (left *y*-axis) and of total amount borrowed (right *y*-axis), by terciles of the DMA distribution. The number above a bar is the *p*-value of a test of differences in means between that bar and the one to its left. For example, the 0.064 above the second bar is the *p*-value of a test of the difference between the middle and bottom terciles of the DMA distribution in the number of payday loans. Individuals in the bottom tercile of the distribution of the DMA index have on average approximately 1 payday loan more than individuals in the top tercile of the distribution of DMA. They borrowed on average 3 times as much as was borrowed by those in the top tercile.

Payday loans are rare in the population, so the average level differences in borrowing by quantiles of the DMA distribution may understate the importance of those with low ability in the payday loan market. Indeed, lower-DMA people appear to play an outsized role in this market. Table 5 shows the share of the total amount borrowed by percentile of the DMA distribution. Those in the bottom 10% borrowed 29% of the total. The bottom 20% of the DMA distribution borrowed almost one-half of the total amount borrowed. In contrast, those in the top 10% borrowed less than 1% of the total amount.

The strong association between payday loans and DMA may partly reflect individual differences in preferences or liquidity. Figure 3 documents the association of payday loans and of DMA with these potential confounders. The panels show averages of the number of payday loans (left *y*-axis) and of the percentile rank in the distribution of DMA (right *y*-axis), separately by impatience, present bias, small-stakes risk aversion, and liquidity. A participant's liquidity is the median, across all days, of the daily sum of savings and checking account balances, overdraft limit, and credit card limit minus balance.

[15] Data on wealth and stock market participation come from the survey. Participants reported the value of different types of assets, including stocks. Information about overdraft balances come from the administrative data.

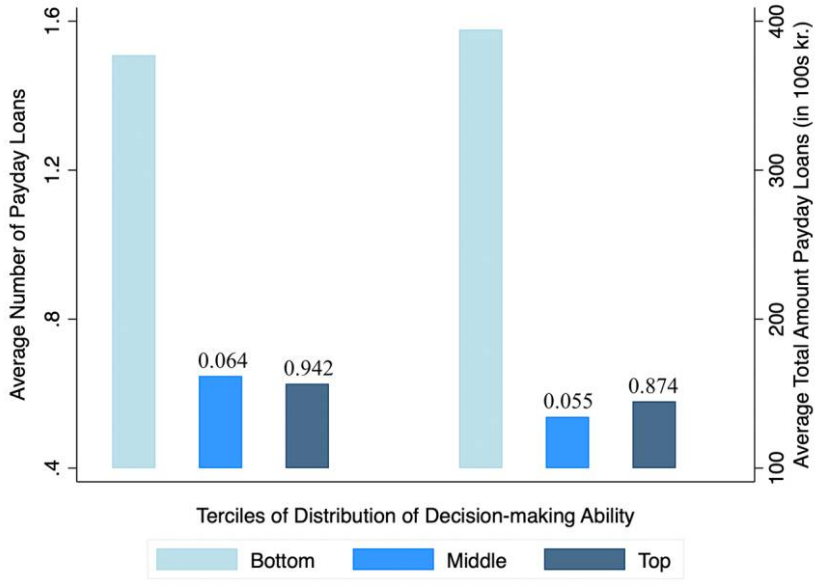

FIG. 2.—Payday loans and DMA. The figure shows the use of payday loan services (over a period of 73 months) by DMA. The three bars on the left show the average number of payday loans per individual for individuals in the bottom, middle, and top terciles of the DMA distribution. The three bars on the right show the average amount per individual of all payday loans for individuals in the bottom, middle, and top terciles of the DMA distribution. Number of participants is equal to 576 in each tercile, for a total of 1,728.

The relationships between payday loan demand, preferences, and liquidity all go in the expected direction. Individuals who are more impatient, more present biased, or have lower liquidity take on average more payday loans. The relationships between DMA and impatience and risk aversion are monotonic: the more impatient and more risk averse exhibit lower DMA. We also find that the present biased exhibit substantially lower DMA than the time consistent. Those in the bottom tercile

TABLE 5
CUMULATIVE SHARE OF TOTAL AMOUNT BORROWED BY PERCENTILE OF DMA DISTRIBUTION

	PERCENTILE OF DECISION-MAKING QUALITY DISTRIBUTION								
	10th	20th	30th	40th	50th	60th	70th	80th	90th
Share (%)	29	45	57	68	76	78	87	89	99

NOTE.—This table shows the share of the total amount of payday loans borrowed by individuals in the bottom *X*th percentile of the DMA distribution as a fraction of the total amount of all payday loans taken by survey participants. For example, together the payday loan borrowers borrowed a total of $388,082. Those individuals in the bottom 20th percentile of the DMA distribution borrowed collectively a total of $174,646. Participants = 1,728.

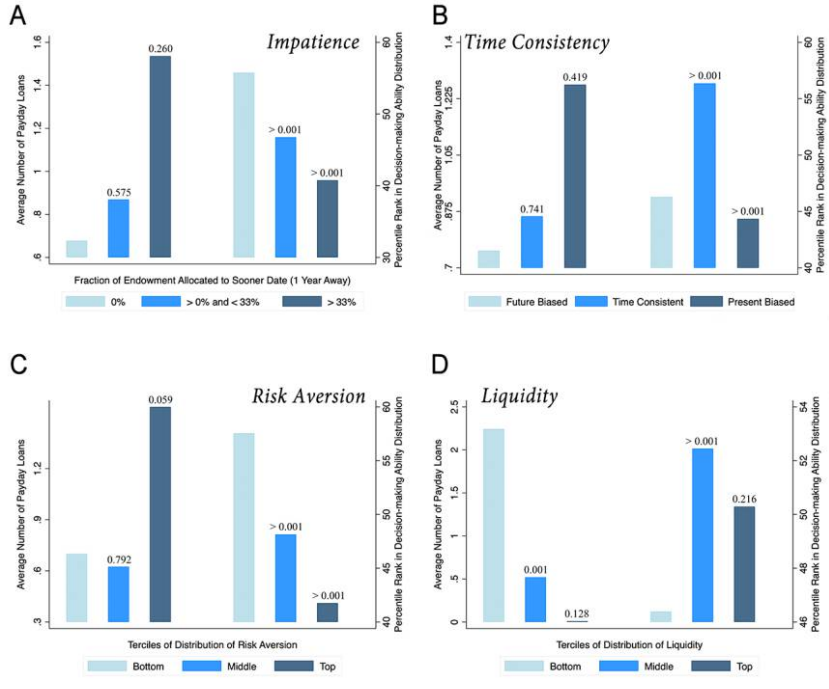

FIG. 3.—Association of payday loans and of DMA with economic preferences and with liquidity. The figure investigates the relationship between number of payday loans and the percentile rank in the distribution of DMA, on one hand, and impatience, time consistency, risk aversion, and liquidity, on the other. The left *y*-axis in the figures shows the average number of payday loans. The right *y*-axis shows the average percentile rank in the distribution of decision-making ability. *A*, separate numbers for those who allocated 0% to the sooner date ($N = 863$); those who allocated more than 0% and less than 33% ($N = 405$); and those who allocated more than 33% ($N = 433$). *B*, separate numbers for those who exhibited future-biased behavior ($N = 535$), time consistency ($N = 686$), and present-biased behavior ($N = 480$) — see section for description of how we constructed these groups. *C, D*, numbers for those in the bottom ($N = 716$ and 535), middle ($N = 514$ and 534), and top ($N = 471$ and 534) terciles of the distribution of risk aversion and of the distribution of liquidity, respectively. The number above a bar reports the *p*-value of a test of the difference between the bar and the bar to its left.

of the distribution of liquidity have lower DMA than those in the middle and top terciles.

The results in figure 3 suggest that the relationship between DMA and payday loans may be confounded by both economic preferences and liquidity. In table 6, we use regression analysis to estimate the relationship between payday loan borrowing and DMA conditioning on these potential confounders. The dependent variable is the number of payday loans. The independent variables shown in the first five rows—DMA, liquidity, impatience, present bias, and risk aversion—are measured in percentile ranks divided by 10, such that the coefficients can be interpreted as the

TABLE 6
LIQUIDITY, DMA, AND PAYDAY LOANS

	Number of Payday Loans				
	(1)	(2)	(3)	(4)	(5)
DMA	−.21	. . .	−.17	−.16	−.16
	(.08)		(.07)	(.07)	(.07)
Liquidity	. . .	−.49	−.48	−.47	−.47
		(.09)	(.09)	(.09)	(.08)
Impatience	. . .	. . .	. . .	.04	.04
				(.04)	(.06)
Present bias	. . .	. . .	. . .	.07	.07
				(.07)	(.07)
Risk aversion	. . .	. . .	. . .	. . .	−9.47E−05
					(.06)
Log income	.05	.67	.69	.69	.69
	(.14)	(.20)	(.21)	(.21)	(.21)
Years of schooling	−.08	−.03	−.02	−.02	−.02
	(.05)	(.05)	(.05)	(.05)	(.05)
Female	−.69	−.82	−.85	−.90	−.90
	(.34)	(.35)	(.35)	(.37)	(.37)
Age	−.01	.01	3.73E−03	1.19E−03	1.20E−03
	(.02)	(.02)	(.02)	(.02)	(.02)
Age^2	−9.09E−04	−2.98E−04	−4.25E−04	−4.99E−04	−4.99E−04
	(6.73E−04)	(6.82E−04)	(6.68E−04)	(6.56E−04)	(6.57E−04)
R^2	.01	.03	.04	.04	.04

NOTE.—This table investigates the relationship between payday loan borrowing, DMA, and liquidity. The mean of the dependent variable is 0.94. DMA, liquidity, time preferences and risk preferences are measured in percentile ranks divided by 10. Observations = 1,573.

effects of increasing these variables by 10 percentiles. The liquidity measure here is the median of the daily sum of checking and savings balances plus overdraft and credit card limits minus the credit card balance. All regressions include controls for the log of average monthly income, years of schooling, gender, age, and age squared.[16]

The results in table 6 suggest that both misfortune and mistake may influence payday loan borrowing. Individuals in worse financial circumstances and with lower DMA take more payday loans. The relationship between payday loans and DMA and the relationship between payday loans and liquidity are robust to controlling for demographics, education, income, and time and risk preferences. In specifications 1–3, DMA is statistically significant at the 5% confidence level. Liquidity is always significant at the 1% level. Improving DMA by 10 percentiles reduces the number of payday loans by 0.16–0.21 loans depending on the specification. Increasing liquidity by 10 percentiles reduces the number of payday

[16] In app. tables 6 and 8, we present the results of alternative specifications that allow for different measures of the potentially confounding variables or nonlinear effects of liquidity. The point estimate of the relationship between DMA and loan demand is stable across specifications.

loans by 0.47–0.49 loans. These estimates are not small given that the average number of payday loans is 0.94 and that as shown in table 6 these loans are concentrated among the individuals with lower DMA.[17]

Impatient and present-biased individuals take more payday loans, but these point estimates are relatively imprecise. Income and gender also have substantial, independent relationships with demand for payday loans. Women take, on average, 1 fewer loan than men, and the point estimate indicates a 10% increase in average income is associated with a 0.07 increase in the number of payday loans received. The counterintuitive, positive relationship with income derives from conditioning on liquidity. The coefficient on income is not statistically distinguishable from 0 with conventional levels of confidence when we do not condition on measures of liquidity.

Appendix table 8 shows that the relationship is robust to controlling for liquidity more flexibly.[18] Appendix table 6 shows, in turn, that the estimated relationship between DMA and payday loans is robust to using alternative measures of demographics, education, liquidity, income, and risk preferences. Finally, appendix table 9 assesses concerns about omitted-variable bias by gradually including controls one a time.

A. Interactions between Misfortune and Mistake

The results in table 6 assume that liquidity and DMA have separable effects on payday loan borrowing, but it is plausible that the influence of one is affected by the level of the other. Figure 4 provides preliminary evidence that this is the case. It divides the sample roughly into quarters by high and low liquidity and by high and low DMA. It then displays the average number of payday loans for each quarter of the sample.

Figure 4 shows that—regardless of DMA—those in the top half of the liquidity distribution virtually never take payday loans. Among the bottom half of the liquidity distribution, however, those with lower DMA take 3 times as many loans as those with higher DMA. Table 7 further investigates these results in a regression framework that controls for demographics, income, and economic preferences.

[17] Applying an instrumental variables (IV) approach to measurement error in DMA (Gillen, Snowberg, and Yariv 2019) suggests that these estimates may be understating the magnitude of the relationship between DMA and payday loans. The approach uses DMA derived from the risk task as an instrument for the DMA derived in the ambiguity task while also using the ambiguity DMA to instrument for the risk DMA. The results of app. table 5 show that the IV point estimate of the relationship between DMA and the number of loans is more than twice the ordinary least squares estimate.

[18] One potential concern is that there are liquid assets that are not reflected in the administrative data, such as shares and bonds. In the survey, participants provided estimates of the value of any assets of this type owned by them. Appendix table 13 shows what happens when we add the value of these assets to our measure of liquidity. They suggest that the omission of such assets may, if anything, overstate the importance of misfortune.

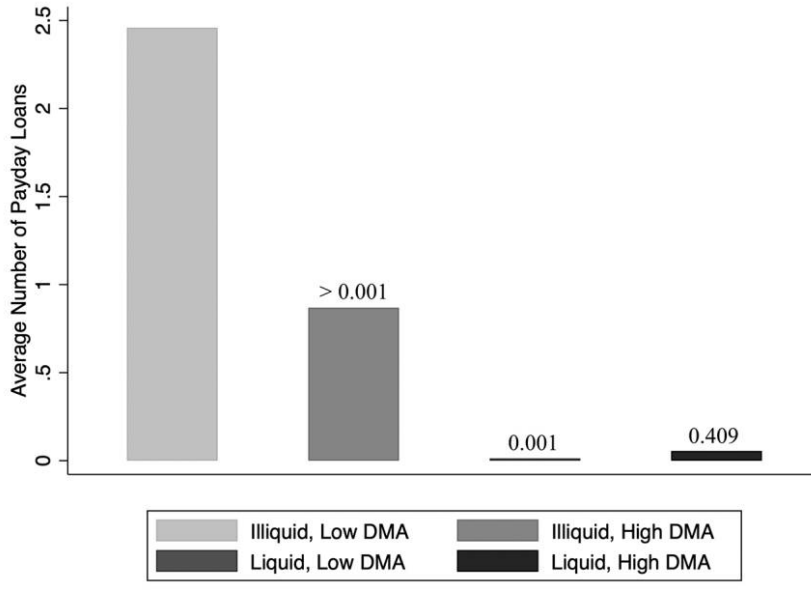

FIG. 4.—Average number of payday loans by liquidity × DMA. The figure shows the average number of payday loans for four different groups: (1) those in the bottom half of the liquidity distribution and the bottom half of the decision-making ability distribution ("Illiquid, Low DMA"); (2) those in the bottom half of the liquidity distribution and the top half of the DMA distribution ("Illiquid, High DMA"); (3) those in the top half of the liquidity distribution and the bottom half of the DMA distribution ("Liquid, Low DMA"); and (4) those in the top half of the liquidity distribution and the top half of the DMA distribution ("Liquid, High DMA"). The number of participants in each group is respectively 484, 443, 384, and 417, for a total of 1,728 participants.

In particular, table 7 presents the results of a regression of the number of payday loans on liquidity, DMA, and the interaction of the two (both are demeaned). The effect of increasing DMA by 10 percentiles is equal to the coefficient on the interaction term times liquidity plus the coefficient on DMA. Similarly, the effect of increasing liquidity by 10 percentiles is equal to the coefficient on the interaction term times DMA plus the coefficient on liquidity. To illustrate, if an individual is at the 60th percentile of the DMA distribution, the effect of reducing liquidity by 10 percentiles is equal to the coefficient on the interaction term minus the coefficient on liquidity.

Column 1 of table 7 reproduces column 3 of table 6 for comparison. In column 2, we add the interaction term. The coefficients on DMA and on liquidity barely change. Time preferences are included in column 3 while risk preferences are included in column 4. These results confirm that higher DMA protects against the negative effects of illiquidity. The coefficient on liquidity in the fourth column is −0.46. The coefficient on the

TABLE 7
INTERACTIVE EFFECTS OF LIQUIDITY AND DMA ON PAYDAY LOANS

	Number of Payday Loans			
	(1)	(2)	(3)	(4)
DMA × liquidity	. . .	.07	.07	.07
		(.02)	(.02)	(.02)
DMA	−.17	−.18	−.16	−.16
	(.07)	(.07)	(.07)	(.07)
Liquidity	−.48	−.47	−.46	−.46
	(.09)	(.08)	(.08)	(.08)
Impatience	. . .	. . .	.03	.03
			(.04)	(.06)
Present bias	. . .	. . .	.07	.07
			(.07)	(.07)
Risk aversion	. . .	. . .	. . .	2.76E−03
				(.06)
Log income	.69	.72	.72	.72
	(.21)	(.21)	(.21)	(.21)
Years of schooling	−.02	−.02	−.02	−.02
	(.05)	(.05)	(.05)	(.05)
Female	−.85	−.78	−.83	−.83
	(.35)	(.35)	(.36)	(.36)
Age	3.73E−03	3.58E−03	1.16E−03	1.05E−03
	(.02)	(.02)	(.02)	(.02)
Age^2	−4.25E−04	−3.62E−04	−4.38E−04	−4.38E−04
	(6.68E−04)	(6.73E−04)	(6.61E−04)	(6.62E−04)
R^2	.04	.05	.05	.05

NOTE.—This table investigates the relationship between payday loan borrowing, DMA, and liquidity. The mean of the dependent variable is 0.94. DMA, liquidity, time preferences and risk preferences are measured in percentile ranks divided by 10. Observations = 1,573.

interaction term, which is statistically significant at the 1% level, is 0.07. This implies that reducing liquidity by 10 percentiles increases the number of payday loans by 0.73 for someone in the 10th percentile of the distribution of DMA, by 0.46 for someone with median DMA, and by 0.18 for someone in the 90th percentile. Similarly, the effect of lower DMA is a decrease in liquidity. Reducing DMA by 10 percentiles increases the number of payday loans by 0.44 for someone in the 10th percentile of the distribution of liquidity and has virtually no effect on the number of payday loans of someone in the 70th percentile.

B. Decision-Making Ability and High-Frequency Variation in Liquidity

The prior results indicate that DMA plays a meaningful role in determining demand for payday loans, especially for those with low average liquidity. These results may, however, overstate the relative importance of DMA and, by implication, mistakes because they account only for an individual's median financial circumstances over a relatively long period. While

DMA may be quite stable over time, liquidity often is not, and averaging over the sample period may gloss over the key liquidity events that drive high-cost credit demand.

To investigate this possibility, we estimate analogous relationships between financial circumstances and high-cost loan demand at the daily level, conditional on demographics, DMA, and preferences. Table 8 presents the results, where the unit of observation is now the individual-day, the dependent variable is an indicator for whether the individual received a payday loan that day, and liquidity is measured on the day before the loan was received. Standard errors on the point estimates are clustered at the level of the individual.

In specification 1 of table 8 we find, as in the low-frequency specifications, a negative relationship between DMA and payday loan demand, conditional on average income, education, and demographics. Given the low probability of taking a loan on any given day, the magnitude of the point estimate is correspondingly smaller but is again statistically distinguishable from 0. In specification 2, we also condition on liquidity levels the day before and find, as expected, a significant negative relationship. Importantly, however, adding this daily measure of the level liquidity has no meaningful impact on the point estimate of the relationship between DMA and payday loan demand. As in the low-frequency specifications, adding controls for preferences in specifications 3 and 4 alters the estimated relationship between DMA and payday loan demand only modestly. To account for the frequency of zeros and outliers in the liquidity distribution, specification 5 replaces the level measure of liquidity with its inverse hyperbolic sign.

Finally, specification 6 evaluates the possibility that the circumstances that represent a liquidity "crisis" depend on an individual's typical liquidity. While each specification has, so far, conditioned on measures of average income and education, the situations that trigger an individual's demand for a payday loan may depend on the extent to which liquidity has fallen below its usual levels. In this last specification, therefore, we replace the daily liquidity level with its within-individual percentile rank. The results show that the relative level of financial circumstances is a significant predictor of payday loan demand but that conditioning on it has little influence on the estimated relationship between DMA and the likelihood of taking a payday loan.[19]

[19] Appendix table 14 presents results that allow for interactive effects of liquidity and DMA at the daily level. Results are qualitatively similar to those in the low-frequency specification of table 7. By estimating the relationship between payday loan demand and liquidity measured at both individual average and individual daily frequencies, we assess the role of both highly persistent and immediate financial circumstances in the decision to take a high-cost loan. In app. table 15, we evaluate a role for intermediate financial circumstances by repeating the analysis in table 8, but at a monthly frequency. The results are qualitatively similar to those at the daily frequency.

C. *The Importance of Prior Mistakes*

A lack of financial resources today could be a consequence of poor decision-making in the past. In this way, earlier mistakes may cause misfortune, which raises concerns about whether the preceding analysis understates the importance of mistakes. Appendix table 10 shows that liquidity is positively associated with DMA. While a test of such a hypothesis is beyond the scope of the paper, there are two pieces of evidence that indicate that mistakes are unlikely to be a primary driver of the misfortune as captured by the measures of liquidity in the previous analysis. First, in table 6, the coefficient on liquidity hardly changes from the second to the third column when DMA is added as a regressor.

The second piece of evidence is illustrated by figure 5. It shows, in particular, how average liquidity measured as a fraction of average daily spending evolves over the month (left *y*-axis). Liquidity is highest in the first four days of the month. Thereafter, it starts declining until the 26th, when it picks up again. The pattern of the demand for payday loans (right *y*-axis) mirrors the pattern of liquidity. The demand is low in the first days of the month when liquidity is high, it increases throughout the month as liquidity gradually declines, and it falls in the last days of the month when liquidity bounces back. In this way, factors related to the calendar, and thus presumably unrelated to DMA, seem to induce large and predictable changes in liquidity that are associated with demand for payday loans. These patterns cast doubt on the idea that prior mistakes are a primary driver of the low liquidity that drives demand for payday loans. Appendix figures 7 and 8 show that these patterns hold both for those with low DMA and for those with high DMA.

In contrast, theories of scarcity (Mullainathan and Shafir 2013; Carvalho, Meier, and Wang 2016) suggest that the importance of mistakes may be overstated. In this view, the many challenges associated with a lack of financial resources may impede cognitive function and degrade the quality of decision-making. If financial scarcity to some extent causes lower decision-making quality, then the regression analyses above will attribute to DMA some of the gross effects of misfortune on payday loan demand.

To evaluate the potential for scarcity effects, figure 6 presents estimates of how our measure of DMA (right *y*-axis) varies with the day of the month in which the participant took the survey. The figure also reproduces the pattern of liquidity over the month shown in figure 5. This analysis provides no evidence of scarcity effects. Those surveyed on especially low-liquidity days exhibit on average the same DMA as those surveyed on higher-liquidity days.

VII. DMA and an Unambiguous Mistake

The preceding results are consistent with the hypothesis that mistakes caused by lower DMA are quantitatively important drivers of demand

TABLE 8
DMA and High-Frequency Variation in Liquidity

	1 if Took a Payday Loan					
	(1)	(2)	(3)	(4)	(5)	(6)
DMA	−1.00	−.99	−.90	−.88	−.80	−.89
	(.41)	(.41)	(.38)	(.38)	(.36)	(.38)
Liquidity in $10,000s	. . .	−.80	−.77	−.76	. . .	. . .
		(.26)	(.24)	(.24)		
IHS of liquidity	. . .	. . .	. . .	. . .	−2.48	. . .
					(.66)	
Pctile rank of liquidity	. . .	. . .	. . .	. . .	. . .	−.37
						(.18)
Impatience	. . .	. . .	.20	.03	.03	.04
			(.23)	(.19)	(.19)	(.19)
Present bias	. . .	. . .	.58	.52	.48	.53
			(.38)	(.38)	(.38)	(.39)
Risk aversion	. . .	. . .	. . .	.25	.16	.28
				(.30)	(.30)	(.30)
Log income	.37	.98	1.08	1.13	2.59	.65
	(.83)	(.89)	(.91)	(.93)	(1.08)	(.89)

Years of schooling	−.30	−.27	−.27	−.27	−.09	−.29
	(.20)	(.20)	(.20)	(.20)	(.18)	(.20)
Female	−3.05	−3.21	−3.60	−3.66	−3.56	−3.51
	(1.85)	(1.88)	(2.01)	(2.01)	(1.97)	(1.99)
Age	−.04	−.03	−.05	−.06	−4.48E−03	−.07
	(.10)	(.10)	(.10)	(.10)	(.10)	(.10)
Age^2	−.01	−4.42E−03	−4.97E−03	−4.97E−03	−4.79E−03	−.01
	(4.33E−03)	(4.26E−03)	(4.19E−03)	(4.19E−03)	(4.19E−03)	(4.3E−03)
R^2	.0005	.0006	.0007	.0007	.0014	.0007

NOTE.—This table controls for more flexible forms of liquidity. It shows results from regressions at the individual-day level. The dependent variable is an indicator for whether participant i took a payday loan on day d. We multiplied it by 10,000 so the coefficients can be interpreted as the effect on a hundredth of a percentage point. Its mean is 3.79. Liquidity refers to the liquidity on the previous day, that is, $d - 1$. Columns 2–4 include liquidity in levels as a control. Column 5 controls for the inverse hyperbolic sine of liquidity. Column 6 adds a within-participant percentile rank measure of liquidity. In particular, the liquidity of participant i on day $d - 1$ was ranked relative to the liquidity of participant i in all other days in the individual time series of the participant. DMA, time preferences, and risk preferences are measured in percentile ranks divided by 10, such that the coefficient gives the effect of an increase of the independent variable in 10 percentiles. The regressions include dummies for day of the week and calendar day of the month. Observations = 1,388,959. Participants = 1,573. Days = 883. Standard errors clustered at the individual level.

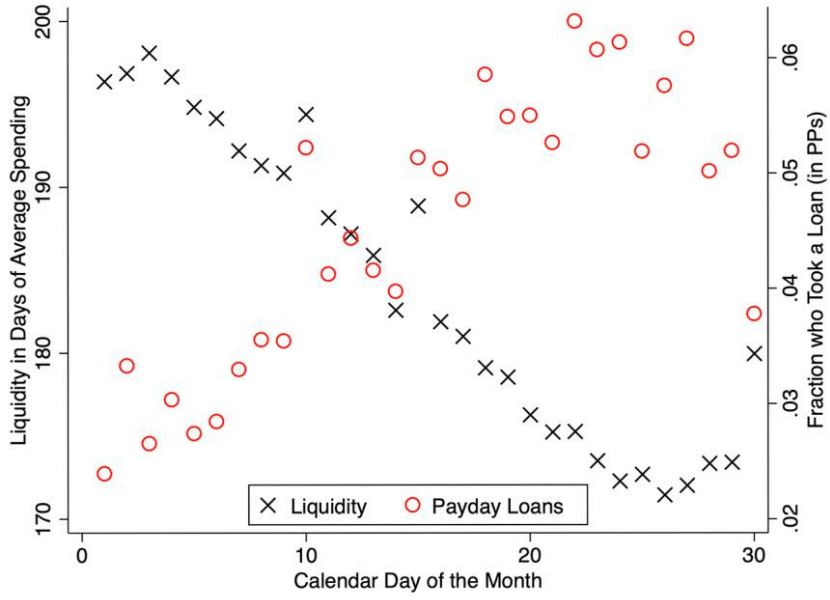

FIG. 5.—Liquidity and demand for payday loans by day of the month. The crosses in the left *y*-axis show average liquidity—measured in days of average spending—by day of the month. The circles in the right *y*-axis show the fraction of individuals who took a payday loan by day of the month. Liquidity observations = 11,068,083. Payday loan observations = 28,274,836.

for payday loans. To further evaluate this hypothesis, we study the relationship between measures of DMA from the experiment and an unambiguous mistake in the administrative data: the accrual of NSF fees.[20] The idea is simple: if mistakes caused by lower DMA are, in part, to blame for high-cost credit demand, then low DMA should also predict other, unambiguous mistakes in the administrative data. The accrual of NSF fees represents just such an unambiguous mistake.

NSF fees are incurred when, in the process of using a debit card to make a purchase, an individual exceeds his or her checking account overdraft limit. The median NSF fee is about $7.50 (see app. table 11 for summary statistics). Note that this may occur even to an individual who has liquidity in the form of another checking account, a savings account, or a credit card. Different from costly overdrafts in markets like the United States, there is no benefit to exceeding the limit because the purchase will not be authorized. A choice that results in an NSF fee is dominated by the decision not to try to make the purchase. Like an American looking left (but not right) before

[20] The correlation between NSF fees and payday loans is 0.08 or 0.09, depending on the specific measures used.

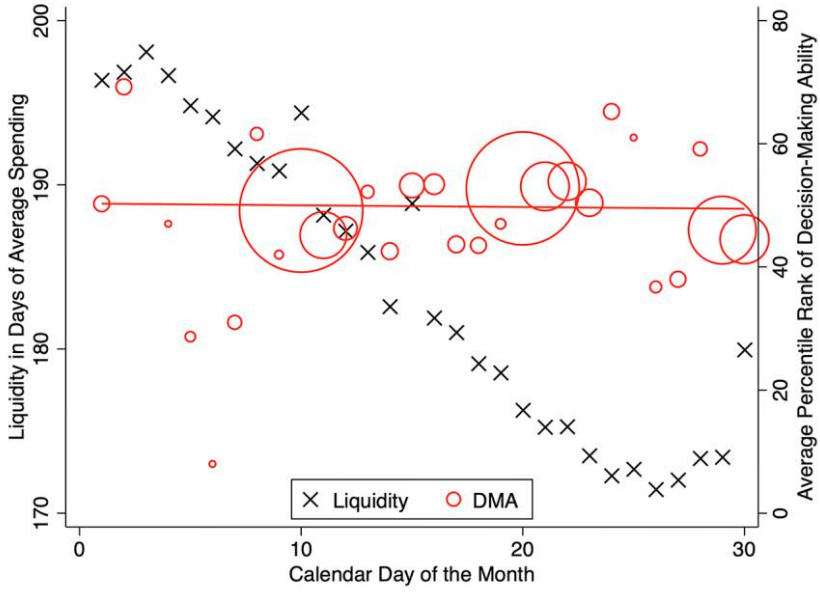

FIG. 6.—The crosses show in the left *y*-axis average liquidity—measured in days of average spending—by day of the month. The circles show in the right *y*-axis average DMA by day of the month. The circumference reflects the number of participants surveyed on that day. Liquidity observations = 11,068,083. DMA observations = 1,728.

crossing the street in the United Kingdom, incurring an NSF fee may be understandable, but would almost universally be viewed as a mistake.

An alternative hypothesis would attribute the correlation between DMA and payday loan demand to an omitted-variables problem. In that view, the estimated relationship between DMA and demand for payday loans is because of a correlation between DMA and unmeasured constraints, preferences, or beliefs that rationalize the demand for payday loans. If that were true, then DMA as measured in the experiment need not predict the unambiguous mistake of NSF fees.

Table 9 shows that the measure of DMA is indeed predictive of the unambiguous mistake of incurring NSF fees. A reduction in DMA by 10 percentiles increases the number of NSF charges by 0.17–0.23 (relative to a base rate of 2.43). Liquidity is also associated with NSF charges: a reduction in liquidity by 10 percentiles increases the number of NSF charges by 0.54–0.57. Interestingly, the interaction between DMA and liquidity is not statistically distinguishable from 0 at conventional levels of confidence. Even among those with liquidity, individuals with lower DMA are more likely to engage in this imperfection.

The accrual of NSF fees appears to receive less attention in policy debate than do payday loans. This analysis indicates, however, that the

TABLE 9
NSF Charges and DMA

	Number of NSF Charges					
DMA × liquidity	. . .	. . .	. . .	. . .	.02	.02
					(.03)	(.03)
DMA	−.23	. . .	−.19	−.17	−.19	−.17
	(.08)		(.08)	(.08)	(.08)	(.08)
Liquidity	. . .	−.57	−.55	−.54	−.55	−.54
		(.09)	(.09)	(.09)	(.09)	(.09)
Impatience	. . .	. . .	. . .	−.06	. . .	−.07
				(.07)		(.07)
Present bias	. . .	. . .	. . .	−.10	. . .	−.10
				(.08)		(.08)
Risk aversion	. . .	. . .	. . .	.16	. . .	.17
				(.08)		(.08)
Log income	.22	1.04	1.07	1.10	1.08	1.11
	(.30)	(.32)	(.33)	(.33)	(.33)	(.33)
Years of schooling	−.09	−.04	−.03	−.02	−.03	−.02
	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)
Female	.04	−.08	−.12	−.16	−.10	−.14
	(.41)	(.40)	(.40)	(.40)	(.39)	(.39)
Age	.05	.08	.07	.06	.07	.06
	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
Age^2	−4.70E−03	−3.98E−03	−4.11E−03	−4.08E−03	−4.09E−03	−4.06E−03
	(9.58E−04)	(9.24E−04)	(9.23E−04)	(9.38E−04)	(9.28E−04)	(9.42E−04)
R^2	.02	.05	.05	.06	.05	.06

Note.—This table investigates the relationship between NSF charges, DMA, and liquidity. The mean of the dependent variable is 2.43. DMA, liquidity, time preferences and risk preferences are measured in percentile ranks divided by 10. Observations = 1,542.

two behaviors may merit more equal footing. Each appears to emerge from both misfortune and mistake. Each thus seems to be a target for both policies aimed at reducing market imperfections that make financial products and services needlessly expensive, and for policies, like mandatory overdraft warning systems, that can help consumers avoid mistakes while still allowing liquidity to flow to those who need it most.

VIII. External Relevance: Results from US Survey Data

The combination of administrative and survey data from Iceland has advantages for studying the relationships between economic circumstances, DMA, and demand for high-cost credit. The administrative data offer high-frequency, accurate measures of economic circumstances and demand for a relatively large, long, and balanced panel. The survey data provide rich measures of preferences and DMA derived from multiple decision domains. One potential concern, though, is that Iceland is a small economy and its people and markets may have distinctive characteristics that limit the external relevance of findings derived from them.

To assess external relevance, we turn to survey data from the United States and compare, to the extent possible, the relationships between economic circumstances, DMA, and demand for high-cost credit in those data with the analogous evidence from Iceland. The US data are drawn from the Understanding America Study (UAS), an Internet panel with respondents aged 18 and older living in the United States.[21] About twice a month, respondents receive an email with a request to visit the UAS site and complete questionnaires. Regular questionnaires collect self-reported economic and demographic information. Two supplementary UAS questionnaires first fielded in 2015 have asked respondents whether they have a payday loan or have had one in the past year. A third survey administered Choi et al.'s (2014) choice-under-risk experiment. See the appendix, available online, for more details.

Combining responses from these three supplements with information from regular UAS questionnaires, we can estimate the relationship among self-reported economic circumstances; preferences and DMA, as revealed in the choice-under-risk experiment;[22] and self-reported demand for this kind of high-cost credit. Table 10 presents the results from the UAS alongside analogous estimates from the Icelandic data.

[21] Respondents are recruited by address-based sampling. Those without Internet access at the time of recruitment are provided tablets and Internet access.

[22] Because UAS participants were administered only a risk task, we are limited in the UAS to measuring preferences with risk tolerance and DMA with consistency with maximization of a utility function that satisfies a dominance principle.

TABLE 10
DMA and Payday Loan Demand in Iceland and the United States

	1 if Had Payday Loan							
	Iceland (1)	UAS (2)	Iceland (3)	UAS (4)	Iceland (5)	UAS (6)	Iceland (7)	UAS (8)
DMA	−.41	−.53	−.55	−.55	−.49	−.39	−.36	−.42
	(.19)	(.11)	(.20)	(.12)	(.20)	(.12)	(.20)	(.11)
Risk aversion	. . .	. . .	. . .	. . .	. . .	. . .	.53	.16
							(.17)	(.11)
Log income	. . .	. . .	. . .	. . .	−.17	−.68	.01	−.66
					(.63)	(.26)	(.62)	(.26)
Years of schooling	. . .	. . .	. . .	. . .	−.53	−.80	−.50	−.79
					(.19)	(.16)	(.19)	(.16)
Female	. . .	. . .	−1.31	2.47	−1.14	2.20	−1.55	2.10
			(1.10)	(.71)	(1.13)	(.71)	(1.13)	(.71)
Age	. . .	. . .	−.14	−.16	−.14	−.16	−.17	−.16
			(.05)	(.03)	(.06)	(.03)	(.06)	(.03)
Age^2	. . .	. . .	−1.43E−03	−1.64E−04	−3.41E−03	−2.07E−04	−3.60E−03	−1.93E−04
			(2.50E−03)	(1.49E−03)	(2.80E−03)	(1.49E−03)	(2.8E−03)	(1.49E−03)
R^2	.003	.005	.010	.019	.017	.030	.024	.030

Note.—This table compares the relationship between DMA and payday loan demand in US data from the UAS with the analogous evidence from Iceland. The dependent variable in the former is an indicator variable for whether the participant had had a payday loan in the past year. In the latter, the dependent variable is an indicator for whether the participant had a payday loan during a 6-year period. The dependent variables were multiplied by 100, such that the coefficients are in percentage points. The mean of the dependent variable is 4.89 in Iceland and 5.05 in the UAS. DMA and risk aversion are measured in percentile ranks divided by 10, such that the coefficient gives the effect of increasing decision-making ability or risk aversion in 10 percentiles. For example, the coefficient in column 1 implies that an increase in DMA in 10 percentiles is associated with a reduction in 0.41 percentage points in the probability of having a payday loan. In Iceland, the number of participants is 1,573. The UAS data are longitudinal with two waves. The number of observations is 5,243 and the number of participants is 2,954 (not all participants were surveyed in both waves). Standard errors are clustered at the individual level in the UAS. Robust standard errors are estimated for Iceland.

The point estimates are similar in the Icelandic and US data. The unconditional correlation between the percentile rank of the DMA distribution and the probability of taking a loan is −0.41 in Iceland and −0.53 in the US data. Conditioning on several economic and demographic variables, and on a measure of risk aversion, brings the point estimate to −0.36 in the Icelandic data and to −0.42 in the US data. Coefficients on the other variables are qualitatively similar in the two datasets, with the exception of gender. In the US, women are approximately 2 percentage points more likely to report that they have or have had a payday loan while the (relatively imprecise) point estimate in Iceland is approximately −1.3. We view the similarities of the two sets of estimates, taken together, as evidence of the external relevance of the richer set of results derived from the Icelandic data. The results also contribute to an emerging literature examining differences in the quality of administrative and survey data (Mas and Pallais 2017; Wiswall and Zafar 2018; Parker and Souleles 2019).[23]

IX. Conclusion

Motivated by the debate on regulation of the high-cost credit market, this paper evaluated the relationship between adverse financial conditions ("misfortune"), imperfect decision-making ("mistakes"), and the demand for high-cost credit. The policy debate revolves around efforts to restrict the circumstances under which individuals may obtain high-cost credit and the possibility that many choices to take such loans are imperfect. Advocates of regulation see high-cost credit as too often exploiting unsophisticated borrowers who would be better off without the loans. Opponents of the regulation see this form of credit as serving those who are in acute need of liquidity and who find it difficult to obtain elsewhere.

Advancing the debate is difficult in part because mistakes are typically hard to identify. Unobserved constraints, preferences, or beliefs can justify many behaviors as optimal, including the demand for high-cost credit. We addressed this identification problem by combining high-quality administrative and experimental data from Iceland. The administrative data describe in detail the financial conditions and behaviors associated with high-cost loan demand. In the experimental data, we manipulated constraints while holding preferences and beliefs constant, which allowed us to identify choice imperfections that provide a measure of DMA.

Evidence from the administrative data alone suggests a substantial but not a dominant role for mistake in driving demand for payday loans.

[23] Ideally, we would have collected in the survey in Iceland self-reported data on payday loans usage to compare to the demand observed in the administrative data. This cleaner comparison should be subject of future work.

Approximately 25% of payday borrowers have a substantial amount of cheaper credit available when they take the loan. These may, however, be conservative tests of mistakes as payday loans may still not be best for those without cheaper forms of credit.

We therefore related high-cost credit demand to measures of DMA along with measures of constraints and preferences. The results show that payday loan borrowers exhibit substantially lower DMA in the experiments; 29% of payday loan dollars are lent to the bottom 10% of the DMA distribution, and 45% are lent to the bottom 20%.

In a regression framework, the relationship between DMA and high-cost loan demand is not explained by demographic characteristics, economic circumstances, or measures of preferences from the experiment, and is mirrored by the relationship between DMA and an unambiguous mistake, the accrual of NSF fees. The external relevance of the Iceland findings is supported by results from a survey of US consumers where the relationship between DMA and the probability of receiving a payday loan is very similar.

Taken together, the results of this study indicate that both misfortune and mistake are important for high-cost credit demand and the accrual of NSF fees. The role of misfortune justifies policy that works to address market imperfections that either make this credit market incomplete or inhibit high-frequency liquidity management by consumers. The role of mistake justifies policy that better equips consumers to avoid any harm from mistakenly choosing to take a high-cost loan or incurring an NSF fee. More specifically, given the importance of both misfortune and mistake implied by these results, efforts at consumer protection should seek ways to avoid limiting trade entirely in this credit market or sharply limiting the size or frequency of NSF fees. The results suggest, instead, that regulators ought to consider lighter forms of paternalism, such as cooling-off periods, certification that the borrower understands a loan's terms, or mandatory overdraft warning systems, to help consumers avoid mistakes while still allowing liquidity to flow to those who need it most (Loewenstein and Haisley 2008).

Data Availability

Code replicating the tables and figures in this article can be found in Carvalho, Olafsson, and Silverman (2023) in the Harvard Dataverse, https://doi.org/10.7910/DVN/1ENX6C.

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